EmoChat: Emotion Analysis Driven Conversational AI

CS 133: HRI - Final Report

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Abstract: In this paper, we propose our framework *EmoChat*, an emotion analysis driven approach to conversational AI. Where traditional forms of conversational AI simply interface users with Large Language Models, *EmoChat* adds an extra step to this interface by first predicting the classified emotion of user input before prompting the AI agent accordingly. The purpose of this study was to examine whether this form of explicit prompting with emotion analysis models would improve the overall empathy exhibited by conversational AI (more specifically, under verbal interactions with robots). With baseline trials conducted with traditional conversational AI and experimental runs with *EmoChat*, the results of our surveys noted that participants tended to find robotic interaction using *EmoChat* to perform more empathetically. More specifically, users found that *EmoChat* allowed the robot (*Misty* robot for this study) to use more appropriate language / facial expressions as well as handle more emotionally intensive tasks.

Introduction

Empathetic robots have been a popular topic in human-robot interaction over the years, with wide application potential in fields such as companion and psychological treatments. Showing empathy requires robots to be able to perceive human emotions. Common ways for human emotion recognition include sentiment analysis, facial emotion recognition, gesture recognition, etc. Another important part for empathetic robots is reacting properly according to human emotions. This can be achieved in multiple ways, such as carefully designed pre-set action and response databases (Hwang et al. 2023), combining multiple interaction methods, etc. Recent developments in large language models give empathetic robots the potential to respond more accurately and better sense human emotions. In this paper, we present Emochat, an empathetic robotic framework that combines sentiment analysis with generative AI to control both the robot's verbal and gestural responses. We conduct experiments to verify our framework's effectiveness and discuss the potential strengths and weaknesses of empathetic robots with generative AI.

Background

Sentiment analysis has served as a main way to sense human emotions for developing empathetic robots, showing promising results in increasing effectiveness and engagement in human-robot interaction(accuracy ([2], [13] [9][11]). Recent research has particularly focused on finding more novel ways to tailor sentiment analysis engines so that they not only operate more accurately but are also able to leverage the emotional sentiment of user input to facilitate more natural human-robot interaction. Researchers have looked into using more complex models like bidirectional LSTM ([1]), or using models pre-trained on domain-specific data or models with multiclass classification of emotions ([5]; [7]). [For this project, the multiclass emotion classification model is used to extract the user's emotion before prompting the conversational AI agent.] Such efforts to improve the use of sentiment analysis in human-robot interactions have demonstrated notable enhancements beyond the more traditional forms of sentiment analysis in HRI. However, robots still largely struggle in interactions when user emotions aren't explicitly expressed in the syntax of their responses ([12]). Also, when applied to social robots or empathetic robots, they can only choose empathetic responses from a pre-selected set, which may affect the robot's ability to personalize its response to human emotions.

On the other hand, recent progress in LLM(Large language model) has led to a significant breakthrough in Human-robot interaction. LLM can understand natural language and give human-like responses. The precision and diversity of LLM response lead to great application potential in multiple HRI fields. Researchers have developed emotional and empathetic robots that use LLM capability to enhance their performance. ([8]) Application of empathetic robots with LLM capability includes psychiatry([3]), psychological counseling([4]), company , and elderly care([6]), showing that LLM can have a promising performance when handling emotional intensive tasks. Also, research shows that empathetic behavior can increase human trust in AI agents, resulting in better interaction efficiency ([10]). While multiple studies have developed empathetic robots using LLM, and researchers have studied the capability of LLM to sense human emotions([14]). Few attempts are made to integrate sentiment analysis and LLM to provide an enhanced empathetic robot with the ability to generate personalized responses.

Algorithm

EmoChat: Emotion-driven Conversational AI

EmoChat proposes a conversational algorithm which leverages emotion analysis and prompt engineering to improve the empathy exhibited by robots in their respective interactions with human subjects. In this experiment, EmoChat is primarily responsible for facilitating the emotion analysis driven conversation between Misty and the participants; and is later tested against more traditional conversational AI for comparison.

In traditional conversational AI, the AI agent is simply prompted by the participant's input and the subsequent response is then returned either via speech or text. However, Emochat first classifies the user's expressed emotion and incorporates it into the prompt processed by the AI agent [*Fig. 1*]. For this experimental use case, the AI agent is also responsible for generating Misty's robotic actions associated with the returned response. These actions allow the AI agent to modulate the robot's facial expressions and arm movements. Our hypothesis suggests that explicitly prompting the AI agent with the analyzed user emotion will improve the overall empathy exhibited by robots (e.g. Misty).

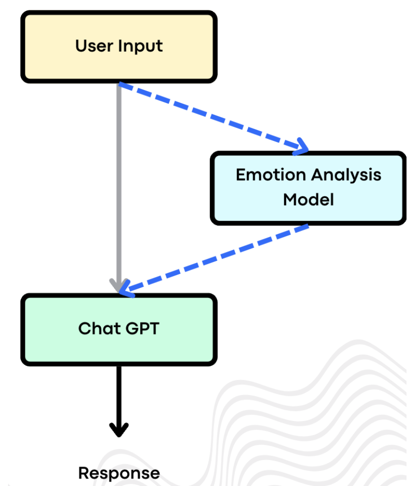

Figure 1: EmoChat Diagram

Assumptions

This experiment relied on 2 variations of the same conversational framework. In both variations, the user conversed with Misty via a computer interface where they could manually type in their responses on a command line. After each input, Misty responded with speech output and emotes accordingly until the end of the conversation.

Under the traditional framework, Misty robot began by introducing itself and asking the participant to speak on something that's been bothering them lately. After 4 "turns" (i.e. after Misty responded to the participant's input 4 times), the AI agent was prompted to formally end the conversation. In comparison, EmoChat is a modified framework which expands upon the existing method by including emotion analysis metrics for both generating the verbal AI response as well as Misty's robotic emotes.

Under this experiment, OpenAI's GPT-4 API was used as the conversational AI agent for both frameworks. Hugging Face's RoBERTa multiclass emotion model was used to process user emotion (the model returns one of 28 unique emotions based on user input). Misty was used at the experimental robot which users interfaced with.

Problem Formulation

This experiment seeked to compare the participants' survey results under 2 conversation types: one with emotion analysis (EmoChat), and one without (traditional conversational AI). At the end of each conversation, the participant was administered a Likert Scale Survey to assess their perception of the robot's ability to empathize and process user emotions. We hypothesized that human-robot conversational interaction via EmoChat would yield results on the Likert Scale Surveys that indicated more robotic empathy when compared to an interaction driven by traditional mode of conversational AI. .

Hypothesis

Misty's responses and actions generated by EmoChat (incorporating emotion analysis for AI prompting) will be perceived as more empathetic by participants compared to Misty's response from the traditional mode of AI.

Algorithm Outline

Under the formal definition of EmoChat, the following are noted:

- **prompt_openAI** is a method that takes in the participant's input and prompts OpenAI for a response based on additional parameters. These parameters include response_type (which can be "follow_up" or "end") and emotion (which must be one of the 28 unique emotions returned by the RoBERTa model).

  1. If the **response_type** is "follow_up", the AI agent is prompted to end the response with a follow up question for the participant. Otherwise, if the response_type is "end", the AI agent simply ends the conversation after its response.
  2. If the **emotion** is None, then the AI agent is prompted without any explicit information regarding the classified emotion of the user's response. Otherwise, the AI agent will be prompted to respond given the processed user emotion.
  3. This method **outputs** the response of the AI agent according to the input. The response is limited to 150 tokens (i.e. $\sim$ 110 words). It also outputs a list of robot movements for Misty to execute along with the response.
  4. *Note:* When prompt_openAI is called, the function sends a prompt which contains the user input, analyzed emotion, and the Misty action set to OpenAI. The sample format of the prompt used is as follows: [User Emotion: <emotion>, respond to user and choose Misty's actions from following set: <misty action set>]: <User input>

- **get_emotion** is a method that takes in textual input, and uses RoBERTa's multiclass emotion model to return the classified emotion associated with the user input. The returned emotion can be one of 28 unique emotions that are pre-set by the model (RoBERTa Hugging Face Doc).

- **emote_behavior** is a method that takes in the robotic actions chosen by the AI agent, and calls the respective actions via Misty's API. Misty has a stored set of potential behaviors which the AI agent can choose from when prompted, each of which is then called for performing here.

The following pseudocode outlines the main driver code that toggled the trial runs between EmoChat and the traditional AI driven conversation algorithm.

Algorithm 1 Main Driver Algorithm

```
# Args: framework = "EmoChat" OR "Traditional AI"

# Robot Intro
misty_robot.text_to_speech(robot_intro)

# Start Conversation
for i in range(4) do
    # Get User Input
    user_input = input(\Participant:  ")

    # Get User Emotion
    emotion = None
    if framework == "EmoChat" then:
        emotion = get_emotion(user_input)
    end if

    # Get OpenAI Response
    response_type = "end" if i==4 else "follow_up"
    openai_response, misty_actions = prompt_openAI(user_input,
              response_type=response_type, emotion=emotion)

    # Robot Response
    emote_behavior(misty_actions)
    print("Misty:\, openai_response)
    misty_robot.text_to_speech(openai_response)
end for
```

Methodology

Robot Hardware & Software Design:

Misty is an open robotics platform that is suitable for social robot development. It is a mini humanoid robot with wheels for moving. Misty has two simple arms, with only 1 degree of freedom each, to show basic gestures. The low degree of freedom enables OpenAI to control the robot's gestures more easily. Misty has a screen for showing facial expressions, as well as other information. It also features pre-built facial expressions, which is beneficial for development. Misty supports multiple coding languages, including python, which is crucial for implementing AI-based behavior algorithms.

Apart from the verbal response, empathetic gestures and facial expressions were also incorporated. Instead of hard coding expressions according to expressed sentiments, the empathetic expressions were generated using OpenAI for both frameworks. Empathetic responses of the robot were broken up into blocks, e.g., lift left arm, eyes wide open, smiley mouth. Each of these "behavior blocks" was stored in a modified class definition and could be selected using OpenAI.

Our emotion analysis model classified the user input using a Hugging Face multiclass emotion analysis model which was trained using the RoBERTa language model. The model returned one of 28 unique emotions (e.g. neutral, confusion, disappointment) which was associated with the user input that was passed in. Under the EmoChat framework, the analyzed emotion from the RoBERTa model was passed into the GPT-4 model alongside the user input - in order to obtain a response for Misty to convey back to the user.

Experimental Design

Each participant in this study engaged in two different interactions with Misty the robot. In both interactions, the participant was required to converse with the robot, then fill out a Likert Scale Survey regarding how well the robot exhibited empathy (Fig. 2). In the experimental interaction, the EmoChat algorithm was used by Misty to generate emotes and verbal responses based on the classified emotion of the user's input. In the control interaction, the traditional AI algorithm was used instead to generate Misty's responses without the use of additional emotion analysis. The order of the two interactions was randomized between users to help avoid ordering effects.

EmoChat Survey
CS 133: Human Robot Interaction

Instructions: Please answer the following questions to your best ability regarding the interaction with Misty that you just had. Each question can be answered on a scale from 1 to 7 - please fill in or circle the one which you feel best describes your experience.

Q1: How empathetic was the robot towards your responses?						
(1) apathetic	(2)	(3)	(4) neutral	(5)	(6)	(7) empathetic

Q2: How competent was the robot's emotional processing?						
(1) incompetent	(2)	(3)	(4) moderate	(5)	(6)	(7) competent

Q3: How well did the Robot emulate human conversational behaviors?						
(1) Failed	(2)	(3)	(4) moderate	(5)	(6)	(7) succeeded

Q4: How appropriately did the robot's language fit the conversation?						
(1) inappropriate	(2)	(3)	(4) moderate	(5)	(6)	(7) appropriate

Q5: How appropriately did the robot's facial expressions and emotes fit the conversation?						
(1) inappropriate	(2)	(3)	(4) moderate	(5)	(6)	(7) appropriate

Q6: Do you think Misty had a comprehensive understanding of the conversation?						
(1) Failed to understand	(2)	(3)	(4) Moderate understanding	(5)	(6)	(7) Completely understood

Q7: Would you trust the robot to handle emotionally intensive tasks?						
(1) Not at all	(2)	(3)	(4) Maybe some tasks	(5)	(6)	(7) Yes-completely

Experimental Run: (control) / (experimental)

Figure 2: Likert Scale Survey

Experimental Setup

Prior to starting the experiments, participants were informed that they would have 2 consecutive conversations with Misty the robot. Each participant was then seated at a desk with a computer interface positioned in front of them on the left, and with Misty the robot placed on the right side of the desk. Upon starting either of the two interactions, Misty spoke to the participant saying "Hi, I am Misty. I'm an experimental robot trying to learn more about humans and their daily activities. Tell me about something that's been bothering you lately." The rest of the details to the experiment are highlighted below in the example experimental procedure:

Experimental Procedure

1. **EmoChat Interaction:** The participant engages in a 4-response long conversation with Misty using EmoChat for response + emote generation.

2. After the first interaction ends, the participant is administered the Likert Scale Survey outlined above.

3. **Traditional AI Interaction:** The participant engages in a second 4-response long conversation with Misty using the traditional AI algorithm for response generation.

4. After the second interaction ends, the participant is administered the same Likert Scale Survey outlined above.

5. The experiment ends, the participant is free to leave

Metrics

In order to measure participant experience, we primarily relied on data collected from the Likert Scale Surveys administered after each interaction. This allowed us to gauge the effect of emotion-aware AI behavior on human evaluation of Misty's exhibited empathy. The conditions of our hypothesis proposed that the Likert scale values would, on average, be higher under the EmoChat framework compared to the traditional framework.

Thus, the results of the two Likert Scale Surveys were aggregated across all participants to examine statistically significant differences in the survey results between the experimental and control interaction. In order to examine these results, we compared average Likert Scale Scores and standard deviations between the two modes of interaction. Additional t-tests were also used to assess the significance of differences in perceived empathy between the two versions of Misty.

Participants

For this study 12 college age students from Tufts University were recruited at random. The age range of the participants ran from ages 19 to 24. Within the pool of participants, 7 were female identifying and 5 were male identifying.

Results

After the survey results were aggregated for all 12 participants, the following parameters were computed for each question under the experimental and control runs: average, minimum, maximum, median (Q2), first quartile value (Q1), and third quartile value (Q3). This allowed us to plot the average and boxplot range of the survey data collected.

We can first look at the results of the first 2 questions [*Fig. 3* and *Fig. 4*]- asking participants (1) how empathetic the robot was towards their response and (2) how competent the robot's emotional processing was. The results for the EmoChat run are in blue, and the results for the control run are in red.

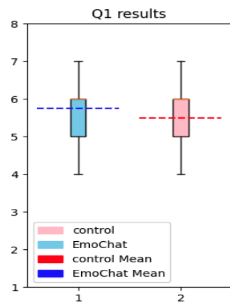

Figure 3: Q1 Results

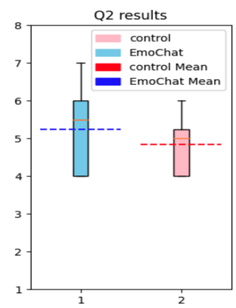

Figure 4: Q2 Results

As is observable, the results for these two questions indicate under both frameworks, participants found Misty to be relatively empathetic and competent at emotional processing. It is worth noting that even early on we see that results under the EmoChat framework yielded slightly higher results on average than under the control framework.

Under the next set of questions, we can look at the comparable results in response to questions 3 through 5, answering: (3) how well the robot emulated human conversational behaviors, (4) how appropriately the robot's language fit the conversation, and (5) how apppropriately the robot's facial expressions / emotes fit the conversation. [*Fig. 5 - 7*]

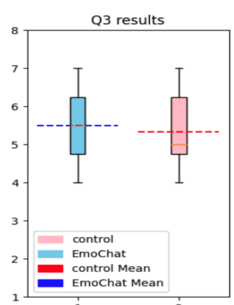

Figure 5: Q3

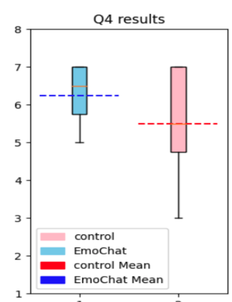

Figure 6: Q4

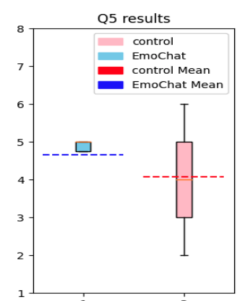

Figure 7: Q5

It is worth noting here that answers to questions 4 and 5 demonstrate that EmoChat trial runs yielded significantly higher scores on average (almost a whole step higher on the 7 point scale). This indicates that under the EmoChat framework, users felt that Misty exhibited more appropriate language, facial expressions, and emotes that better fit the conversation.

Under the last 2 questions answered in the surveys, we can look at experimental differences in response to the following questions: (6) whether Misty had a comprehensive understanding of the conversation, and (7) whether the user would trust Misty to handle emotionally intensive tasks [*Fig. 8* and *Fig. 9*].

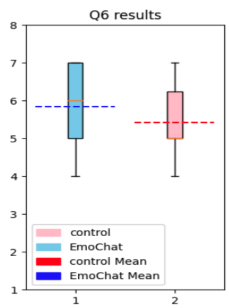

Figure 8: Q6 Results

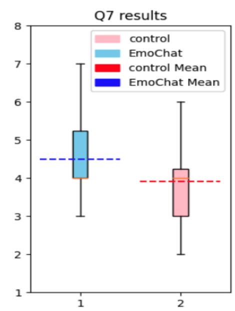

Figure 9: Q7 Results

While results for answers to Q6 yielded pretty mild improvements under EmoChat, answers to Q7 show pretty significant differences (almost a whole unit difference on average between EmoChat and control results). The significant difference on average as well as from the median / range of provided answers to Question 7 indicate that users tended to trust Misty more with emotionally intensive tasks after interaction under the EmoChat framework.

From analyzing the results of this study, it is important to note that all metrics collected under EmoChat had yielded higher results on average compared to the control run administered to the 12 participants. While some average differences between the two trial runs by question were milder, survey results under questions 4, 5, and 7 demonstrated EmoChat's potential for improving the emotional / empathetic abilities exhibited by Misty.

These results are further explored below.

Discussion

Per the experimental results, answers to all 7 questions under both trial runs suggest that interactions with Misty under the EmoChat framework generally yielded more empathetic responses. The results averaged across all 12 participants are plotted below (blue being average question results for the EmoChat trials, and red for the trials utilizing traditional conversational AI) [*Fig. 10*].

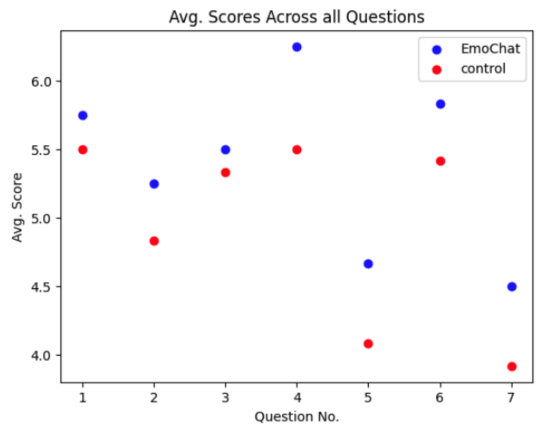

Figure 10: Avg. Survey Scores

There are two primary takeaways from this figure that support this assertion. Firstly, the averaged results under the EmoChat framework all yielded higher scores in comparison to the traditional AI interactions. The second aspect to these results resides in the degree to which the survey results differred with and without the EmoChat framework.

For one, the range of results across both experimental conditions were relatively consistent. None of the average results fell below a "4" level rating - meaning, for the most part, both the traditional AI and emotion analysis driven frameworks yielded generally mid to positive feedback regarding Misty's exhibited empathy. Upon observing the trends within the graph, one could also observe the degree to which the survey answers differred. In particular, results between the control and EmoChat survey answers never varied by more than 1 level within the 7 point Likert scale. This lets us know that while EmoChat demonstrates the potential to improve the general extent of empathy exhibted by Misty, it likely does not alter the distribution of results over the 7 questions in the survey.

To gain a better understanding of how EmoChat improves the level of empathy exhibited by Misty, we computed the differences between the averaged survey results of the control and EmoChat trials. The averaged differences between the two trial types were plotted below [*Fig. 11*]:

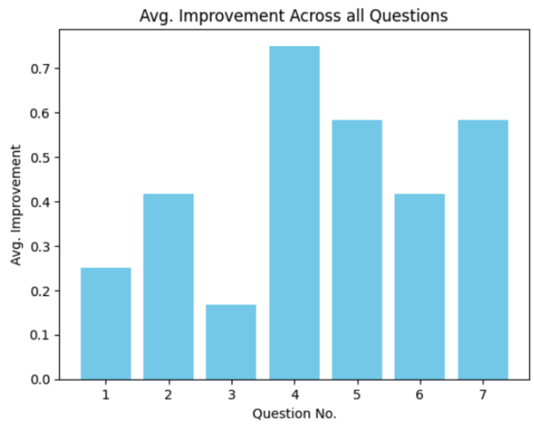

Figure 11: Avg. Score Improvements via EmoChat

As previously noted, none of the average scores under both trial types differed by more than 1 unit within the 7 point Likert Scale. That being said, results under the EmoChat trials seemed to demonstrate more notable improvement in averaged survey scores for some questions than others. While Questions 1, 2, 3, and 6 only saw an average improvement between 0.2 and 0.4 on survey answers, the answers for questions 4, 5, and 7 saw the most improvement. Answers to Question 5 and 7 demonstrate that EmoChat improved the average survey score by about 0.55, while question 4 saw an improvement of more than 0.7.

Looking back on the structure of the survey questions [*Fig. 2*], we can get a deeper insight into what aspects of empathy EmoChat (emotion analysis driven conversational AI) actually improves from the baseline metrics. While Questions 1, 2, 3, and 6 had more to do with Misty's grasp on emotional processing and understanding of conversational behaviors, Questions 4 and 5 specifically ask the user whether they found Misty's language and facial expressions / emotes appropriate for the conversation. Likewise, Question 7 asks the user whether they would trust Misty to handle emotionally intensive tasks. It is also worth noting that averaged survey results under questions 5 and 7 for the traditional conversational AI trial yielded lowest of the averaged scores across all questions types (around a 4.0). Taking this all into account, we suggest that EmoChat as a framework (leveraging emotion analysis for explicit AI prompting) shows promise in terms fine tuning Misty's ability to use more appropriate language and paralinguistics (e.g. facial expressions / etmoes) to fit the conversation. It is likely that the added emotion analysis allows Misty to generally handle more emotionally intensive tasks - thereby increasing survey results for Question 7.

By use of emotion analysis driven conversational AI, we suggest that use of appropriate language / paralinuistics coupled with emotional robustness has allowed Misty's exhibited empathy to improve. That is to say that, our proposition via our hypotheses is corroborated by the analyzed results. Trials under

EmoChat yielded higher average survey results across all answered question types (by about 1 unit on the 7 point likert scale). Particularly, EmoChat had likely allowed Misty better usage of appropriate language / emotes and better ability to handle emotionally intensive tasks [via results of *Fig. 11*]. Thus - according to our results, use of the EmoChat framework has in fact improved the exhibited empathy within Misty's responses, compared to the traditional mode of conversational AI.

These conclusions, however, would likely need further testing regardless - provided the limited sample size of this study. Within this study, we were only able to collect data from 12 separate students (all of which were from the same age range from our university). Further experimentation and study would be needed to confirm the results of this experiment.

Conclusion

The comprehensive analysis of the survey results obtained from the experimental and control runs presents intriguing insights into the impact of EmoChat, an emotion-driven conversational AI framework, on the perceived empathy of Misty's responses. The comparison of survey results across the EmoChat and traditional AI trial types provided valuable perspectives on Misty's performance under both frameworks.

Initially, the examination of the first two questions showed consistent findings: Misty was perceived as empathetic and competent in emotional processing under both EmoChat and the control framework. However, EmoChat consistently yielded slightly higher average results, setting an early trend. The subsequent questions delved deeper into Misty's conversational abilities and appropriateness of language, facial expressions, and handling emotionally intensive tasks. Notably, EmoChat significantly outperformed the control framework in questions 4, 5, and 7, indicating enhanced appropriateness in language and expressions as well as increased trust in Misty for emotionally intensive tasks.

The discussion section further illuminated these findings. While both frameworks maintained generally positive feedback regarding Misty's empathy, EmoChat consistently surpassed the traditional AI in eliciting higher scores. The differences observed across all survey questions, approximately a one-unit shift on the Likert scale, suggested EmoChat's potential to enhance Misty's empathy without altering the overall distribution of survey results. The detailed exploration into the improvement via EmoChat also revealed varying degrees of enhancement across different survey questions. The experimental results and subsequent analysis supported our initial hypothesis that EmoChat, leveraging emotion analysis for conversational AI prompting, elevates Misty's perceived empathy.

The consistent pattern of higher average scores across all question types, particularly in language usage, expressions, and handling emotionally intensive tasks, substantiates this claim. However, as aforementioned, the study's limited sample size of 12 participants from a specific demographic necessitates further experimentation for conclusive validation. Expanding the study across diverse demographics and conducting additional trials would fortify these conclusions.

Overall, the evidence suggests that EmoChat serves as a promising framework to augment Misty's empathetic responses, showcasing its potential in improving emotional understanding, language appropriateness, and adeptness in handling emotionally intense tasks.

Acknowledgements

Contributions under each team member:

Jonathan Lai:

- Wrote main driver code and AI Engine module (handles primary prompt engineering, calling OpenAI, and related processing)
- Designed Likert Scale Survey
- Conducted Analyses of Results (created all graphics)
- Wrote Abstract, Algorithm, Methodology, Results, and Discussion section of paper
- Conducted Experimental Runs for Data collection
- Created Presentation Slides

Shijie:

- Wrote all robotics code (Modified Misty Class) and handled Text to speech module
- Primarily responsible for Literature Review and reading on related works
- Wrote Introduction, Background, and Robotic Hardware Section of paper
- Conducted Experimental Runs for Data collection

Turner Hayes:

- Wrote code for sentiment analysis, emotion analysis, and set up interactions between OpenAI server and our code.
- Wrote Conclusion section of paper
- Conducted Experimental Runs for Data collection

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Resources

Github Link: EmoChat Code
EmoChat Demo Video: Google Video Link